

# A survey of AI in finance

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## ABSTRACT

In recent years, the dramatically fast development of financial technology (fintech) has played an important role in the production, delivery and consumption of financial products and services. In this survey, we sum up the primary research discoveries in fintech area, which include the possible evolution of fintech's effect on customer protection, prosperity and the discovery of the asset prices and returns, and the design of digital frameworks in the era of the fintech.

## ARTICLE HISTORY

Received 3 April 2022

Accepted 10 May 2022

## KEYWORDS

Financial technology; asset pricing; credit risk; digital banking

## 1. Introduction

In recent years, the dramatically fast development of financial technology (fintech) has played an important role in the production, delivery and consumption of financial products and services. Due to its potential large impact on the entire financial ecosystem, the innovation of the fintech has been widely and heavily discussed in recent years. The financial industry has observed an exciting and impressive transformation. In this review, we aim to describe the primary aspects of this transformation and the functionality of fintech in the mainstream sector of the financial market, as well as its related impact on consumers and the whole financial eco-system.

The activities of fintech companies have made fast evolution and entered into almost all sectors of the financial system. Consumers have been benefited from the innovative financial services by fintech companies, while the efficiency of the whole financial system has been significantly improved. At the same time, attentions and concerns have also been aroused by regulators about many aspects of the services provided by fintech companies, which sometimes very much likely play the role of a bank. In addition, there are legal challenges and ethical concerns related to financial technology around consumer privacy and the impact that financial technology may have on the stability of the entire financial ecosystem. Although fintech can greatly enhance the credit risk evaluation and improve the efficiency of the financial system by faster, better quality and lower cost services, the risks of it cannot be entirely avoided.

This survey paper also contributes to the special issue of 'Financial Technology and Artificial Intelligence in Finance' on the *Journal of Chinese Economic and Business Studies* (JCEBS). The special issue conference was organized by the University of Edinburgh Business School, Chinese Economics Association CEA UK, and Xi'an

Jiaotong-Liverpool University business school on 16 October 2020. The conference was held online, and the recorded talks are publicly available via JCEBS Special Issue Conference I and JCEBS Special Issue Conference II. The conference has five keynote speakers from academia and financial industry, including Morgan Stanley, Deutsche Boerse Group London, BlackRock Hong Kong, Franklin Templeton Investments UK and the Centre for Computational Finance and Economic Agents (CCFEA) at the University of Essex. In addition, it has four academic paper presentations from Peking University, Salford University, Northwest A&F University and Jinan University.

The keynote speeches are all focused on the cutting edge application of machine learning in financial markets. Dr Jian Chen, head of Quant in FX trading desk at Morgan Stanley, discussed how machine learning can be used in FX trading and how Morgan Stanley use trading-bot on FX market. He particularly addressed the importance of the explainability of the machine learning models in trading areas. Dr Yauheniya Shynkevich, data scientist at Deutsche Boerse Group London, introduced the application of machine learning in clearing house operation efficiency improvement. Similarly, Dr Lily Lee, trading desk analyst at BlackRock, Hong Kong, discussed the trading cost analysis using machine learning. Finally, Dr Alistair Haig, quantitative investment researcher at Franklin Templeton Investments UK, discussed interesting comparison studies between human analyst's mind and machine learning's decision. All keynote speeches point out the irresistible trend of applying machine learning technology in financial market. People usually call it financial technology or fintech.

The special issue of 'Financial Technology and Artificial Intelligence in Finance' on the *Journal of Chinese Economic and Business Studies* includes five papers. Three of them fall in the AI applications in financial markets and two papers address the digital economics development status in China.

Jiang et al. (2022) investigate the herding problem before and during the COVID-19 on Hong Kong market using CCK-based OLS and quantile regression with the estimation of the magnitude of herding by HS model. This study documents the change of the herding phenomenon before and after the COVID-19 and confirms the detection sensitivity on the magnitude and variation of the herding problem.

Yousuf and Zhai (2022) particularly investigate the interconnections among crude oil and global equity markets using DCC-GARCH model. It documents the weakened shock transmission over time before the COVID-19 and a doubled strength during the pandemic.

Tsang (2022) proposes a new mechanism for modelling and observing the tick-data in high-frequency finance. The proposed directional change is based on the ad-hoc threshold and provides a novel data-driven framework for providing new information about the tick-to-tick data.

The work of Rahman and Islam and Liu focuses on the digital economy area. Rahman and Islam investigate the impact and attraction of voluntary insurance, a new digital product, on the users' adoption of the digital banking system. Liu (2022) addresses an overall picture of AI application's influences on China's economy and particularly on the network economy effect by constructing a new AI economic growth model. This paper provides a decent summary of the research paradigm of digital economy based on value, network and consensus.

In this survey, we further sum up the primary research discoveries in fintech area up until this point, the possible evolution of fintech's effect on customer protection, prosperity and the discovery of the asset prices and returns, and the design of digital frameworks in the era of fintech. The design of the remainder of this paper is as per the following. [Section 2](#) summarises the recent work of AI in Quantitative Finance, Credit Valuation and Digital Banking. [Section 3](#) discusses the future direction of this fast evolving area and concludes.

## 2. Literature on AI in finance

### 2.1. *AI in quantitative finance*

An ever-increasing number of literature uses AI as innovation in the finance area, particularly in equity return forecasting, asset pricing, risk management and corporate governance.

Early works use complex machine learning models as a pure data fitting tool with no financial theories. Such work has been widely seen in predicting original stock prices or directional movements. The early work, i.e., Fischer and Krauss (2018), documents the significantly outperforming forecasting capability of the recurrent neural network such as (LSTM) against conventional deep neural network and simpler statistical models, such as logistic regression and random forest. In addition, Krauss, Do, and Huck (2017) recognize the stacked models (ensemble model) constructed by conventional models including random forests, decision trees and neural network highly outperforming other models in forecasting probabilities of equity returns and achieving good investment returns. Those literary works altogether fall into the specialized investigation of using financial data and information in complex models and thus vigorously add to information science writings instead of the contribution of financial areas.

Another direction of financial literature regards factors as hidden and unobserved ones and computes utilizing statistical methods including principal component analysis (PCA), i.e., local PCA and instrumented PCA (IPCA). The IPCA is proposed by Kelly, Pruitt, and Su (2019) for extracting systematic  $\beta$  for all latent factors. The systematic  $\beta$  are calculated by the instrumented principal component analysis using hundreds of fundamental characteristics of stocks. Similarly, Lettau and Pelger (2020) propose a PCA-based statistical method called 'Risk-Premium PCA' (RP-PCA) to directly consider the objective for extracting the latent factors, the explanation of the cross-sectional expected returns. RP-PCA uses a penalty term to control the pricing error for searching the latent factors that can explain both the expected return and covariance structure. The work of Kelly, Pruitt, and Su (2019) and Lettau and Pelger (2020) is still based on the conventional asset pricing theories with linear assumption between the factor and the risk exposure. However, such linearity relation is relaxed by the work of Gu, Kelly, and Xiu (2021), which introduces a neural-network-based estimator to extract the latent factor and the corresponding risk exposures. Following this trend, Chen, Pelger, and Zhu (2019) and Bryzgalova, Pelger, and Zhu (2020) propose a Generative-Adversarial-Network-based model and a decision-tree-based forest model, respectively, to generate stochastic discount factors for classical asset pricing model structure.

In addition to the extensive and in-depth applications in equity market, machine-learning-based models are also observed in applications in other asset pricing areas, such as bond risk premium forecasting Bianchi et al. (2021), cross-sectional bond return prediction Nazemi, Baumann, and Fabozzi (2022) and defaulted corporate bonds recovery rate estimation Guo et al. (2021).

In recent years, the wide application of machine learning technology in quantitative investment strategy makes many people think that it is bound to become the future of investment management. However, it is found that quantitative investment strategy based on machine learning often plays a good role in the environment with stable overall trend and rich and regular volatility, but the effect is often very poor in the event of extreme crises or accidents, such as the quantitative crash in the week of 6 August 2007 Khandani and Lo (2008), and the flash crash on 6 May 2010.

During the flash crash, in the 33 minutes from 2:32 p.m. EST, the U.S. stock market experienced one of the most volatile periods in history. Kirilenko et al. (2011) analyse the flash crash event using the data of all 15,000 accounts of e-mini trading on the same day. They found that the response of algorithmic trading procedures to extreme selling pressure exacerbated the decline in prices. Just a few minutes before flash crash, the market-driven algorithm produced a seriously unbalanced trading order under the action of market signals seriously deviated from the fundamental track, resulting in the collapse of trading institutions due to selling pressure. Another incident related to algorithmic trading is Knight Capital, one of the largest market makers in the U.S. stock market. Its trading error on 1 August 2012 resulted in the accumulation of a large number of stock positions within 45 minutes of the beginning of the trading day, resulting in a final loss of \$456.7 million and almost bankruptcy.

## **2.2. *AI in credit valuation***

Although machine learning models have been widely used in asset pricing, they have also been applied to risk management areas, especially in the field of credit risk valuation for a longer time.

### **2.2.1. *Credit scoring and risk***

A very early work of Desai, Crook, and Overstreet (1996) investigates the learning ability of the neural networks and linear discriminant analysis and logistic regression, in evaluating the credit scores for small-sized loan. It is the first work that documents the customized neural networks as having a very promising avenue in correctly identifying the bad loans. Crook, Edelman, and Thomas (2007) further extend their own work to the credit screening area by investigating the performance of conventional machine learning models including logistic regression and support vector machine. Afterwards, this area of study is extended to predict loss given default of corporate bonds Yao, Crook, and Andreeva (2015, 2017) using support vector regression models. In recent years, the application of credit evaluation model based on machine learning has been expanded to SME loans and mortgage areas, i.e., the works of Jagtiani and Lemieux (2019), Goldstein, Jagtiani, and Klein (2019) and Croux et al. (2020).

In addition, natural language processing (NLP) is used to analyze the text information written by the borrower on the loan platform, so as to understand the borrower's language style and their potential issues, such as the work of Gao, Lin, and Sias (2018). They found that if borrowers' textual information are more readable, more aggressive and contained a lower level of deception, lenders would bid more actively, be more likely to extend credit and charge lower interest rates. Based on alternative data, the use of machine learning model in credit evaluation and decision-making can improve consumers' access to the loan. However, there are some potential risks, such as the use of alternative data may lead to ethical bias, such as race and gender.

Consistent with these findings, Berg et al. (2020) uses a machine learning model to analyze the borrower's digital footprint information, such as activity records left on the Internet. The work of Berg et al. (2020) shows that these digital footprints are very effective in predicting consumers' default. The combination of digital footprint and traditional loan evaluation variables can significantly improve the overall prediction ability of the model, which shows that the digital footprint information provides a sufficient and effective supplement to the borrower's standard information. Therefore, banks and other lending institutions can enhance their credit and risk pricing decisions by viewing traditional risk scores and alternative data, so as to reduce potential risks.

Ant Financial, a Chinese financial technology giant, and Tencent's pay points credit have established a new credit scoring system based on alternative data collected from non-traditional information sources such as social media, online shopping, payment applications and mobile accounts. This type of scoring provides a more comprehensive assessment of the borrower's financial life, and can effectively help borrowers who lack credit history fill the credit gap and obtain loans.

### **2.2.2. Peer-to-peer lending**

With the gradual establishment and promotion of credit risk assessment mechanism based on machine learning model, a new lending method, peer-to-peer lending (P2P), has gradually become a new financing channel with strong attraction to consumers and small enterprises in the past decade. P2P loan platform directly matches investors and borrowers through the supply and demand of funds, and eliminates intermediaries to facilitate transactions. Both the work of Balyuk (2016); Chava, Paradkar, and Zhang (2018) found that P2P loan channels significantly improved the access to credit for consumers who could not obtain credit from traditional banks. Such loan services have penetrated into areas where traditional banks may not provide enough services, such as highly concentrated markets and areas with few bank branches per capita Jagtiani and Lemieux (2018).

The research work of Ramcharan and Crowe (2013) and Butler, Cornaggia, and Gurun (2017) shows that in the P2P lending risk assessment mechanism, in addition to the standard financial variables, the influence of much personal soft information of the borrower is helpful for the borrower to make credit decisions. However, those personal soft information include race, age and personal outlook Ravina, (2019); social capital Lin and Pursiainen (2018); hometown Lin and Viswanathan (2016) and social network Lin, Prabhala, and Viswanathan (2013). These factors will significantly affect the lender's decision-making in terms of ex-ante loan pricing, loan amount and post-loan results. However, under fair lending and consumer privacy regulations, more and more such information is prohibited in credit decisions.

### 2.3. Digital banking

The progress of financial science and technology has made remarkable achievements in social development, one of which is financial inclusion services. Financial inclusion refers to helping vulnerable group of people establish channels to use formal financial services. This group of people mainly includes low-income people, vulnerable people, people with missing credit data, people living in rural areas, women and young people. Due to the large number of individuals in these groups and the growing social needs, financial inclusion has become a subject of increasing concern. The inherent defects of traditional banking include information asymmetry, incomplete institutional coverage and the lack of basic infrastructure required for banking in many regions. Research shows that the overall level of economic development, the rationality of the financial system, the degree of credit data sharing and openness and the degree of financial inclusion and the elimination of financial poverty are positively correlated (Beck, Demirgüç-Kunt, and Levine, 2007).

The rapid development of fintech technology can promote financial inclusion at the social level in different ways. Due to Kenya's significant progress in financial inclusion, Allen et al. (2021) study the overall information of its bank community penetration and financial access threshold. Between 2006 and 2010, the emergence of private equity banks had a positive and significant impact on the use of bank accounts and credit opportunities by Kenyan households. Private equity banking is a creative private institution that has designed a banking service for low-income and poorly educated customers and underserved areas. The number of deposit and loan accounts of equity banks accounts for 50% and 30% of the total deposit and loan accounts in Kenya, respectively. The successful business model of Kenya equity bank has provided solutions to the financing problems of small and medium-sized enterprises and individuals in many African countries. Similarly, the credit business of Ant financial services to small- and medium-sized enterprises and individuals under Alibaba, a Chinese e-commerce platform, has promoted China's financial inclusion Hau et al. (2018). Ant financial services complement the credit needs of small enterprises with low credit scores in the credit market through cooperation with regional commercial banks. Among them, the application of fintech technology can allow borrowers to more fully evaluate the risk factors of customers, and small and medium-sized enterprises that get more praise from customers in online business operations may be more favored by borrowers.

Fintech helps ease local credit supply frictions in the credit market and extends the 'frontier' of credit availability to small businesses with low credit scores. In addition, these online e-commerce platforms promote a self selection process in which more funds tend to be directed to online merchants whose customers get better ratings Huang, Li, and Shan (2019).

In terms of financial inclusion, the British government may be the first country in the world to introduce policy changes at the national level. The UK Government has been looking at ways in which established large banks and building societies could make it easier for new financial services providers to offer new products, services and a better choice for customers. One of these ways is called 'Open Banking' Open Banking Limited (2022). Open Banking is intended to make it easier for companies to offer different and innovative services while giving consumers more choice and more control over their

money and financial information. All of this will be achieved by requiring banks and building societies to make certain information accessible to other approved companies in a standardised, straightforward, and secure way and only ever with customer's explicit consent. Nine largest UK retail banks and building societies, including Barclays plc, Lloyds Banking Group plc, Santander, Danske, HSBC, RBS, BoI, Nationwide and AIBG, have a legal requirement to allow certain information to be shared securely online with other regulated companies through Open Banking. Banking data is shared through APIs between the banks and the fintech startup partners. Competition and Markets Authority (CMA) believes that open banking enables consumers to share information, and companies can also provide efficient payment methods and innovative products to the Competition and Markets Authority (2021).

In this process, the bank is undergoing transformation and upgrading in the following four aspects. The first is the transformation from offline to online. Benefiting from this round of technological revolution, banks can start more business online and provide customers with digital and intelligent service experience, so that customers can enjoy contactless financial services without leaving home, rather than going to offline outlets. It is worry-saving, labor-saving and convenient. It is also more applicable in emergencies such as epidemics. The second is to change from product-oriented to customer-oriented. If the traditional bank is more like a 'business', first build products and services, and let customers come to the bank to choose according to their own needs, then the current market pattern encourages banks to turn into 'business', take the customer experience as the driving force, take the initiative to go to customers, explore customer needs and develop more customized products accordingly. Third, from a fully functional independent system to an open platform. With the promotion of technical force, the bank is no longer an 'isolated island' and no longer creates all the ecology alone. Instead, it allows the finance to really integrate into the scene service and spread the functions of the finance to all the places needed. As a part of the overall market, the bank will build a coordinated and orderly ecosystem with other enterprises. Fourth, from emphasizing assets and neglecting transactions to neglecting assets and emphasizing transactions. Just because it is no longer an independent system, the development of the bank will no longer rely on the simple expansion of asset scale, but will meet the diversified needs of customers. Starting from the customer's business model and transaction chain, focusing on the customer's daily business activities, it will provide the whole process services covering demand docking, scheme design, product delivery and continuous follow-up, and rely on data technology to build a richer business system. From focusing on assets to focusing on transactions, banks will be able to obtain more income and higher efficiency with less assets and capital, and continuously improve the utilization efficiency of assets and capital.

Britain has become the main force in the development of European Open banking. Since then, Europe has formulated a series of general guidelines for the development of open banking, which have been accepted by all regions of the world. At present, the open banking ecosystem in Europe is the most perfect, which is not only due to the active policies of the European Union and European governments but also due to the positive response of major European banks and the continuous efforts of middle-level enterprises to quickly establish an open ecosystem. In November 2015, the EU issued the payment service directive 2 (hereinafter referred to as PSD2), which formulated the rules for the



opening of payment accounts, providing a legislative basis for the EU's open banks. In March 2016, the United Kingdom officially released the 'the open banking standard' OB2016 (2016), which put forward three standards of open banking (data standard, API standard and security standard) and a governance model (the cornerstone of maintaining the effective operation of open banking standards) to guide how to create, share and use open banking data. At present, the regulations and standards formulated by the EU and other European countries have become the guidelines for the development of global open banks.

From the perspective of open ecological structure, in terms of regulators, various legal frameworks and regulatory systems are relatively mature, which can make the middle layer and account layer faster clarify the business scope and red line set by law, so as to better formulate strategies. The middle layer provides a good environment for the competition and development of the account layer, mainly focusing on the technical level, that is, it provides various solutions for banks and financial institutions in the account layer to integrate APIs. For example, truelayer provides an open data API platform, which is connected to many major banks and financial institutions in the UK. The account layer responded positively, led by the traditional big banks represented by BBVA, and took the lead in establishing an open API platform, which has become one of the earliest successful cases of digital transformation of traditional banks. In order to compete for the market, other financial institutions have also joined the pace of digital transformation. The two complement each other, supplemented by the basic support provided by the ecological layer, and the rapid development of open banking.

In 2016, BBVA officially launched the open API platform. In the trial operation stage, nearly 1600 enterprises and developers participated in the security and user experience test of the platform to ensure a safe development environment and excellent partner use experience. In May 2017, BBVA made its first strategic achievement in the process of promoting the opening of banks. BBVA API was officially put into use in the Spanish market, opening three types of APIs, including six APIs based on retail customer information, one API based on enterprise information and one API integrating various channel data at the retail end, BBVA has also become the first bank in the world to realize the commercial operation of open API.

## **2.4. AI for economic development**

Artificial intelligence is widely and deeply used in all aspects of social and economic life, including urban planning, logistics, local political and economic life, agriculture and higher education.

In a modern society with increasingly complex business processes and increasingly fierce business competition, the significance of global supply chain for each country and society is self-evident. Maintaining a stable and efficient global supply chain is facing unprecedented pressure. AI plays a more and more important role in modern global supply chain, such as cognitive automation of detail oriented repetitive tasks in the company's back office, Richardson (2020), prediction of logistics demand and delay Chen et al. (2021).



In addition to supply chain application, a World Bank report found that AI technology based on natural language processing analysis (NLP) can be used to analyze the written records of village gatherings in developing countries such as India to determine the topics discussed, and track how the flow of conversation changes with the gender and status of speakers, so as to clarify the operation of these deliberative bodies. Using AI technology such as NLP can effectively promote accountability in local political and economic life (Parthasarathy et al. 2017).

AI technology also contributes to the assessment of local and global development levels by many countries and international organizations, including extracting important indicator components, monitoring different development indicators of various countries, classifying the common attributes of different national development plans, predicting their development trends and behaviors and do on Gupta et al. (2021).

AI also plays an irreplaceable role in helping to analyze the data of the United Nations Sustainability Goal Indicators (SDI) Miller et al. (2020). SDI data include a large number of earth observation data, such as the proportion of forest area in the total land area, the proportion of degraded land in the total land area and the proportion of agricultural area under productive and sustainable agriculture. Collecting such data from countries around the world and effectively analyzing and processing all kinds of unstructured data depend on AI technology. Moreover, AI technology can also be used as an effective tool to monitor the progress and goal realization of the sustainable development project.

AI can also be used in agriculture area. In Kenya, Mozambique and Tanzania, local farmers use the mobile app Nuru integrated with AI algorithm to identify the damage to leaves from the photos taken and send the information to the authorities, so as to help monitor the existence of an invasive pest, which threatens agricultural income and food security throughout East Africa. Such a simple and easy-to-use AI terminal program can change the overall situation of the agricultural economic system in a very small way. In addition, AI-based digital agriculture solution xarvio™ helps the United Nations achieve sustainable development goals through intelligent proportioning and spraying crop fungicides Shankar et al. (2020).

The contribution of AI to social and economic development can also be reflected in the reconstruction of higher education. AI-based automation model can bring more effective and accurate higher education resources. AI with precise positioning and personalized customization is reshaping the higher education industry. The combination of online courses and artificial intelligence can further increase the access of people in poor areas to education and significantly improve the learning and employment level of emerging markets. Educational high-tech companies such as Coursera, Andela and Udemy, the world's leading online education platforms, are collecting academic performance data of students in emerging markets and preparing to use these data to provide them with valuable advice on learning, employment and even entrepreneurship. In India, AI education start-up upGrad has enrolled 2000 students in entrepreneurship, digital marketing, data analysis and product management courses, while education high-tech companies use two-way satellite technology to provide on-site courses for about 2000 primary and secondary schools in the southern state of Karnataka by science, mathematics and English teachers Medina and Schneider (2018).

### 3. Future direction and conclusion

The in-depth research and wide application of machine learning in the financial field is likely to change the future research direction of some financial theories, and even subvert the existing order of the whole financial service system.

In asset pricing, factor model has always been the main framework of empirical analysis of asset pricing. The emergence of machine learning model provides a powerful statistical tool for the construction of next-generation factor model with high-dimensional settings. The progress and insight brought by this technological trend ensure that the factor model will continue to be the core of empirical asset pricing in the next few years.

Machine learning is neither a panacea for financial empirical analysis nor a substitute for economic theoretical modeling. Financial domain knowledge is still an indispensable theoretical basis for asset pricing research using machine learning. The most promising direction of future empirical asset pricing research is the organic integration of financial and economic theory and machine learning model. Such organic integration will further promote the development of asset pricing theory because asset pricing theory focuses on the price formed through the aggregation or evacuation of investor beliefs, which will undoubtedly determine the long-term equilibrium trend of price in some subtle, complex and sometimes surprising way, rather than obvious linear combination. The machine learning model can flexibly adapt to and capture rich and complex information sets. Combined with the asset pricing theoretical model, it can make a more in-depth description of the financial logic of the common theoretical model with low-dimensional factor structure.

The rapid development of fintech has played an important role in the digital transformation of enterprises, the delivery of financial products and services and the mode of consumption. In particular, the emergence and wide use of a large number of alternative data based on consumer consumption habits and financial behavior have promoted the application of machine learning model in the financial field. Convenient access to a large number of alternative data and fast evolving machine learning models have become key factors in promoting innovation in the field of financial technology in recent years, and billions of consumers around the world have benefited from this iterative change. However, these advanced technologies to improve financial life will also bring a series of new risks, such as consumer privacy risk. Therefore, the rapid development of financial technology companies has also led to corresponding problems. The unique alternative data of users can promote the convenience of the borrower to the lender's audit, as well as help in credit for small and medium-sized enterprises and individuals. However, whether and how the services of similar financial products such as risk assessment and credit default assessment provided by related fintech companies should be included in the regulation has become the focus of global discussion. Although advanced technology has brought great benefits to the financial system and all aspects of society, and helped vulnerable people have easier access to financial credit products, it also brings corresponding risks, including ethical privacy risk and the risk of complex cyber attacks. Therefore, the risk management of fintech companies has become more important than ever before. In the foreseeable future, when the services of fintech companies are becoming more and more widely accepted, the traditional banking system will increasingly rely on various services provided by such high-tech companies. As industries

increasingly embrace financial technology innovation and rapid digital transformation, regulatory regulations need to be adjusted in time to keep up with the innovation of new financial technology, fully protect consumers and the overall financial system and continue to shoulder the responsibility of promoting financial technology innovation.

## Acknowledgments

We acknowledge the support provided by the Young Scientists Fund of the National Natural Science Foundation of China (Grant No. 72101207).

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

This work was supported by the Young Scientists Fund [72101207].

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## References

- Allen, F., E. Carletti, R. Cull, J. Q. Qian, L. Senbet, and P. Valenzuela. 2021. "Improving Access to Banking: Evidence from Kenya." *Review of Finance* 25 (2): 403–447. doi:[10.1093/rof/rfaa024](https://doi.org/10.1093/rof/rfaa024).
- Balyuk, T. 2016. *Financial Innovation and Borrowers: Evidence from Peer-to-peer Lending*. Toronto, ON, Canada: University of Toronto-Rotman School of Management.
- Beck, T., A. Demirgüç-Kunt, and R. Levine. 2007. "Finance, Inequality and the Poor." *Journal of Economic Growth* 12 (1): 27–49. doi:[10.1007/s10887-007-9010-6](https://doi.org/10.1007/s10887-007-9010-6).
- Berg, T., V. Burg, A. Gombović, M. Puri, and A. Karolyi. 2020. "On the Rise of Fintechs: Credit Scoring Using Digital Footprints." *The Review of Financial Studies* 33 (7): 2845–2897. doi:[10.1093/rfs/hhz099](https://doi.org/10.1093/rfs/hhz099).
- Bianchi, D., M. Büchner, A. Tamoni, and S. Van Nieuwerburgh. 2021. "Bond Risk Premiums with Machine Learning." *The Review of Financial Studies* 34 (2): 1046–1089. doi:[10.1093/rfs/hhaa062](https://doi.org/10.1093/rfs/hhaa062).
- Bryzgalova, S., M. Pelger, and J. Zhu. 2020. Forest through the Trees: Building Cross-sections of Stock Returns. Available at SSRN 3493458.
- Butler, A. W., J. Cornaggia, and U. G. Gurun. 2017. "Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions?" *Management Science* 63 (12): 4175–4187. doi:[10.1287/mnsc.2016.2560](https://doi.org/10.1287/mnsc.2016.2560).
- Chava, S., N. Paradkar, and Y. Zhang. 2018. Winners and Losers of Marketplace Lending: Evidence from Borrower Credit Dynamics. Georgia Institute of Technology working paper.
- Chen, L., M. Pelger, and J. Zhu. 2019. Deep Learning in Asset Pricing. Available at SSRN 3350138.

- Chen, Y.-T., E. W. Sun, M.-F. Chang, and Y.-B. Lin. 2021. "Pragmatic Real-time Logistics Management with Traffic IoT Infrastructure: Big Data Predictive Analytics of Freight Travel Time for Logistics 4.0." *International Journal of Production Economics* 238: 108157. doi:10.1016/j.ijpe.2021.108157.
- CMA, Competition and Markets Authority. 2021. "Update on Open Banking - Open Banking Implementation Entity." Accessed 18 5 2022. <https://www.gov.uk/government/news/update-on-open-banking>
- Crook, J. N., D. B. Edelman, and L. C. Thomas. 2007. "Recent Developments in Consumer Credit Risk Assessment." *European Journal of Operational Research* 183 (3): 1447–1465. doi:10.1016/j.ejor.2006.09.100.
- Croux, C., J. Jagtiani, T. Korivi, and M. Vulanovic. 2020. "Important Factors Determining Fintech Loan Default: Evidence from a Lendingclub Consumer Platform." *Journal of Economic Behavior & Organization* 173: 270–296. doi:10.1016/j.jebo.2020.03.016.
- Desai, V. S., J. N. Crook, and G. A. Overstreet Jr. 1996. "A Comparison of Neural Networks and Linear Scoring Models in the Credit Union Environment." *European Journal of Operational Research* 95 (1): 24–37. doi:10.1016/0377-2217(95)00246-4.
- Fischer, T., and C. Krauss. 2018. "Deep Learning with Long Short-term Memory Networks for Financial Market Predictions." *European Journal of Operational Research* 270 (2): 654–669. doi:10.1016/j.ejor.2017.11.054.
- Gao, Q., M. Lin, and R. W. Sias. 2018. "Words Matter: The Role of Texts in Online Credit Markets." *Journal of Financial and Quantitative Analysis* forthcoming.
- Goldstein, I., J. Jagtiani, and A. Klein. 2019. "Fintech and the New Financial Landscape". Bank Policy Institute (BPI): Banking Perspectives Q 1.
- Gu, S., B. Kelly, and D. Xiu. 2021. "Autoencoder Asset Pricing Models." *Journal of Econometrics* 222 (1): 429–450. doi:10.1016/j.jeconom.2020.07.009.
- Guo, X., H. Lin, C. Wu, and G. Zhou. 2021. "Predictive Information in Corporate Bond Yields." *Journal of Financial Markets* 100687.
- Gupta, S., S. D. Langhans, S. Domisch, F. Fuso-Nerini, A. Felländer, M. Battaglini, M. Tegmark, and R. Vinuesa. 2021. "Assessing whether Artificial Intelligence Is an Enabler or an Inhibitor of Sustainability at Indicator Level." *Transportation Engineering* 4: 100064. doi:10.1016/j.treng.2021.100064.
- Hau, H., Y. Huang, H. Shan, and Z. Sheng. 2018. "Fintech Credit, Financial Inclusion and Entrepreneurial Growth". Unpublished working paper.
- Huang, Y., Y. Li, and H. Shan. 2019. "The Distributional Effect of Fintech Credit: Evidence from e-Commerce Platform Lending". *Tech. rep., University of Geneva Working Paper*.
- Jagtiani, J., and C. Lemieux. 2018. "Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks?" *Journal of Economics and Business* 100: 43–54. doi:10.1016/j.jeconbus.2018.03.001.
- Jagtiani, J., and C. Lemieux. 2019. "The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lendingclub Consumer Platform." *Financial Management* 48 (4): 1009–1029. doi:10.1111/fima.12295.
- Jiang, R., C. Wen, and Z. Yang. 2022. "Herding Behavior in Hong Kong Stock Market during the Covid-19 Period: A Systematic Detection Approach." *Journal of Chinese Economic and Business Studies*.
- Kelly, B. T., S. Pruitt, and Y. Su. 2019. "Characteristics are Covariances: A Unified Model of Risk and Return." *Journal of Financial Economics* 134 (3): 501–524. doi:10.1016/j.jfineco.2019.05.001.
- Khandani, A. E., and A. W. Lo. 2008. "What Happened to the Quants in August 2007?: Evidence from Factors and Transactions Data". *Tech. rep., National Bureau of Economic Research*.
- Kirilenko, A., P. Kyle, M. Samadi, and T. Tuzun. 2011. "The Flash Crash". *The Impact of High Frequency Trading on an Electronic Market*.
- Krauss, C., X. A. Do, and N. Huck. 2017. "Deep Neural Networks, Gradient-boosted Trees, Random Forests: Statistical Arbitrage on the S&P 500." *European Journal of Operational Research* 259 (2): 689–702. doi:10.1016/j.ejor.2016.10.031.

- Lettau, M., and M. Pelger. 2020. "Estimating Latent asset-pricing Factors." *Journal of Econometrics* 218 (1): 1–31. doi:10.1016/j.jeconom.2019.08.012.
- Lin, M., N. R. Prabhala, and S. Viswanathan. 2013. "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online peer-to-peer Lending." *Management Science* 59 (1): 17–35. doi:10.1287/mnsc.1120.1560.
- Lin, M., and S. Viswanathan. 2016. "Home Bias in Online Investments: An Empirical Study of an Online Crowdfunding Market." *Management Science* 62 (5): 1393–1414. doi:10.1287/mnsc.2015.2206.
- Lin, T.-C., and V. Pursiainen. 2018. "Fund What You Trust? Social Capital and Moral Hazard in Crowdfunding". Social Capital and Moral Hazard in Crowdfunding, July 31
- Liu, Z. 2022. "Development Paradigm of Artificial Intelligence in China from the Perspective of Digital Economics." *Journal of Chinese Economic and Business Studies*.
- Medina, L., and F. Schneider. 2018. "Shadow Economies around the World: What Did We Learn over the Last 20 Years". [www.imf.org/en/Publications/WP/Issues/2018/01/25/Shadow-Economies-Around-the-World-What-Did-We-Learn-Over-the-Last-20-Years-45583](http://www.imf.org/en/Publications/WP/Issues/2018/01/25/Shadow-Economies-Around-the-World-What-Did-We-Learn-Over-the-Last-20-Years-45583)
- Miller, L., M. Bolton, J. Boulton, M. Mintrom, A. Nicholson, C. Rüdiger, R. Skinner, R. Raven, and G. I. Webb. 2020. "AI for Monitoring the Sustainable Development Goals and Supporting and Promoting Action and Policy Development". 2020 IEEE/ITU international conference on artificial intelligence for good (AI4G). IEEE, pp. 180–185.
- Nazemi, A., F. Baumann, and F. J. Fabozzi. 2022. "Intertemporal Defaulted Bond Recoveries Prediction via Machine Learning." *European Journal of Operational Research* 297 (3): 1162–1177. doi:10.1016/j.ejor.2021.06.047.
- OB2016. 2016. "Open Banking API Specification". [standards.openbanking.org.uk/api-specifications/](https://standards.openbanking.org.uk/api-specifications/)
- Open Banking Limited. 2022. Open banking. <https://www.openbanking.org.uk/>
- Parthasarathy, R., V. Rao, and N. Palaniswamy. 2017. "Deliberative Inequality: A text-as-data Study of Tamil Nadu's Village Assemblies". <https://documents.worldbank.org/en/publication/documents-reports/documentdetail/582551498568606865/deliberative-inequality-a-text-as-data-study-of-tamil-nadus-village-assemblies>
- Rahman, A. M., and S. Islam. "Can Voluntary Insurance Ensure risk-free digital-banking in Chinese-economy: Seeking Attentions?" *Journal of Chinese Economic and Business Studies*.
- Ramcharan, R., and C. Crowe. 2013. "The Impact of House Prices on Consumer Credit: Evidence from an Internet Bank." *Journal of Money, Credit and Banking* 45 (6): 1085–1115. doi:10.1111/jmcb.12045.
- Ravina, E., 2019. Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets. Available at SSRN 1107307.
- Richardson, S. 2020. "Cognitive Automation: A New Era of Knowledge Work?" *Business Information Review* 37 (4): 182–189. doi:10.1177/0266382120974601.
- Shankar, P., N. Werner, S. Selinger, and O. Janssen. 2020. "Artificial Intelligence Driven Crop Protection Optimization for Sustainable Agriculture". 2020 IEEE/ITU International Conference on Artificial Intelligence for Good (AI4G) virtual online. IEEE, pp. 1–6.
- Tsang, E. 2022. "Directional Change for Handling tick-to-tick Data." *Journal of Chinese Economic and Business Studies*.
- Yao, X., J. Crook, and G. Andreeva. 2015. "Support Vector Regression for Loss Given Default Modelling." *European Journal of Operational Research* 240 (2): 528–538. doi:10.1016/j.ejor.2014.06.043.
- Yao, X., J. Crook, and G. Andreeva. 2017. "Enhancing two-stage Modelling Methodology for Loss Given Default with Support Vector Machines." *European Journal of Operational Research* 263 (2): 679–689. doi:10.1016/j.ejor.2017.05.017.
- Yousuf, M., and J. Zhai. 2022. "The Financial Interconnectedness between Global Equity Markets, Crude Oil and the GCC." *Journal of Chinese Economic and Business Studies*.